



Original Research Paper

Multivariate Assessment of Soil Functionality Using Integrated Indicators in the Thonnur Kere Distributary, Southern Dry Zone, Karnataka

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Abstract

Intensive farming has resulted in extensive soil degradation in command areas, lowering productivity and disrupting ecological equilibrium. Quantifying spatial variability in soil health is indispensable for sustainable land management. This paper analyzes the spatial variability in soil quality in the Thonnur Kere distributary, Cauvery command area of Karnataka, using Principal Component Analysis (PCA). 300 geo-referenced surface soil samples (depth 0–20 cm) were taken from the upper, middle, and tail-end areas and their physico-chemical and biological parameters were determined. We recognized a distinct textural gradient, moving from sandy loam in the upper part to downstream loam and clay loam, which was correlated with higher bulk density, water-holding capacity, salinity, and pH. Organic carbon and microbial activity decreased downstream, affected by organic matter loss and sedimentation. PCA and the Minimum Data Set (MDS) method emphasized sand content, dehydrogenase activity, and microbial biomass carbon as the most important indicators of soil function. Merging of silhouette scores with Hierarchical Cluster Analysis (HCA) facilitated better regional classification. Increased silhouette values in the middle and end areas indicated high indicator coherence, increasing SQI evaluation ecological usefulness.

Keywords: Minimum Data Set, Principal Component Analysis, Sensitive Index, Soil Properties, and Soil Quality Index

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Introduction

Soil is one of the most important natural resources for maintaining ecological stability, agricultural production, and environmental sustainability (Lal, 1997). It is a nutrient recycler, a dynamic substrate for plant growth, a home for a diverse range of microorganisms, and a water flow regulator (Doran & Parkin, 1994; Karlen et al., 1997). Maintaining soil health has become a top priority due to the growing need for food worldwide, especially in areas with intensive agricultural methods (Bhattacharyya et al., 2015). Thus, ongoing evaluation and improvement of soil quality are necessary for sustainable land management (Bastida et al., 2008).

Within the parameters of a natural or managed ecosystem, soil quality is defined as the soil's capacity to sustain biological production, regulate and divide the flow of water and solutes, filter and buffer pollutants, and support ecological and human health (Karlen et al., 1997). The physical, chemical, and biological properties of soil are all included in this intricate concept; these properties are interconnected and together impact how ecosystems operate (Doran & Zeiss, 2000). The quality of the environment and agricultural yield may suffer if any of these traits worsen (Rattan et al., 2005; Singh et al., 2014). For food security in India, canal-irrigated command areas are essential, particularly in semi-arid regions with irregular and insufficient rainfall (Qadir et al., 2001). Such an agroecological zone is best represented by Southern Dry Zone (SDZ) of Karnataka, which is distinguished by black and red soils, moderate to low rainfall, and a dependence on irrigation from tanks and reservoirs (Sharma et al., 2018). The Mandya district's Thonnur Kere distributary is an example of a canal-irrigated command system in this area, where sugarcane and paddy are grown intensively under constant irrigation. Although these cropping systems enhance short-term productivity, they may also lead to long-term soil degradation due to nutrient imbalances, compaction, salinization, organic matter depletion, and reduced microbial activity (Singh et al., 2013; Fageria et al., 2011).

Even though soil health is important for maintaining agricultural productivity, traditional evaluations in these areas tend to focus mostly on chemical characteristics, frequently ignoring important physical and biological aspects (Bhattacharyya et al., 2015; Bastida et al., 2008). A more comprehensive assessment of soil functional capacity is offered by combining physical (such as texture, bulk density, and porosity), chemical (such as pH, electrical conductivity, and concentrations of macro- and micronutrients), and biological indicators (such as microbial biomass and enzymatic activities like dehydrogenase) (Doran & Zeiss, 2000; Sharma et al., 2018). Principal Component Analysis (PCA) and other multivariate statistical techniques offer a

systematic means of reducing the dimensionality of data and identifying significant indicators of soil quality in this context (Andrews et al., 2002; Bastida et al., 2008). Classifying and comparing soils according to their functional performance is made easier by the creation of a Soil Quality Index (SQI) based on PCA. These index-based frameworks facilitate the development of site-specific management actions and evidence-based decision-making (Karlen et al., 1997; Bhattacharyya et al., 2015). Thus, the goal of the current study was to conduct an integrated evaluation of the soil quality in the Mandya district's Thonnur Kere distributary zone, which is indicative of Karnataka's Southern Dry Zone. The particular goals were to: (i) evaluate the spatial variability in soil quality in the distributary's upper, middle, and tail-end segments; (ii) determine the key indicators that are most susceptible to changes in soil health; and (iii) create a PCA-based SQI for classifying soils according to their functional capacity. The outcomes of this study are intended to inform farmers, extension personnel, and policymakers in the development of targeted soil and nutrient management strategies aimed at enhancing the sustainability of irrigated agroecosystems.

Material and Methods

Experiment site

The Thonnur Kere distributary in Karnataka's Southern Dry Zone (12.4875°N, 76.6422°E) spans 2,150 ha with semi-arid climate, Alfisols and Inceptisols, and irrigated agriculture (mainly paddy and sugarcane) supported by the KRS dam.

Soil sampling and analysis

In January 2024, random soil sampling was conducted across the Thonnur Kere distributary to assess spatial variability in soil quality. A total of 300 samples were collected from 0–20 cm depth across upper, middle, and tail-end regions under paddy and sugarcane cultivation, with GPS coordinates recorded (Figure 1). Samples were pre-processed and analyzed for key physico-chemical and biological properties. Soil pH, EC, BD, and MWHC were determined using standard protocols (Jackson, 1973). Exchangeable cations and CEC were analyzed following Pansu and Gautheyrou (2006), available phosphorus via Olsen and Watanabe (1957), and SOC by Walkley (1947). Particle size was measured using the pipette method (Gee and Bauder, 1986), and available Fe and Zn as per Lindsay and Norvell (1978). Biological indicators included dehydrogenase activity (Casida et al., 1964), urease activity (Bremner, 1972), and MBC using the chloroform fumigation-extraction method (Vance et al., 1987).

Soil Quality Index

PCA and Scoring

Andrews et al. (2002) proposed using Principal Component Analysis (PCA) to select uncorrelated soil quality indicators for developing a Multidimensional Scaling (MDS) model. In this

study, 12 key soil attributes were selected based on their relevance to soil health and crop productivity: pH, EC, OC, P₂O₅, K, Ca, Mg, Na, MWHC, BD, CEC, Fe, and Zn. These indicators influence fertility, root growth, porosity, structure, and stability. Considering the Cauvery command area's susceptibility to salinity and alkalinity, salinity-related parameters like pH, EC, Ca, Mg, and Na were prioritized. PCA retained components with eigenvalues ≥ 1 and $\geq 5\%$ variance. High-loading indicators (within 10% of maximum) were selected. Pearson's correlation ($r > 0.6$) removed redundancy, retaining variables with highest loadings. This ensured a relevant, non-redundant MDS for reliable SQI.

Soil properties were scored using the "more is better," "less is better," and "optimum range" approaches (Lamichhane et al., 2019). OC, CEC, P₂O₅, S, Ca, Mg, K, Fe, Zn, silt, clay, MWHC, dehydrogenase, urease, and MBC followed the "more is better" rule, while BD and Na were "less is better." EC and pH were considered "optimum range" due to their dual impact on plant growth. To standardize data, both linear and non-linear scoring methods were used, following Biswas et al. (2017), with equations based on the respective scoring criteria.

- i) Linear scoring—The indicator scores were assigned based on the 'more is better' and 'less is better' criteria using linear scoring equations (Equations (1) and (2)) as described by Biswas et al., 2017.

Formula (if more is better):

$$\text{Score} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \dots \dots \text{Equation 1}$$

Formula (if less is better):

$$\text{Score} = \frac{X_{\max} - X}{X_{\max} - X_{\min}} \dots \dots \text{Equation 2}$$

LS is the linearly normalized score for the X soil attribute, X is the observed value of the soil property, X_{min} is the minimum observed value of the X soil property, and X_{max} is the maximum observed value of the X soil property.

- ii) Non-linear scoring - The non-linear scoring of variables was and carried out a sigmoidal type function, as outlined in Equation (3), following the methodologies proposed in various studies:

$$\text{Score} = \frac{1}{1 + (V_i/V_m)^b} \dots \dots \text{Equation 3}$$

Where:

X is observed value of soil property, X_{opt} is optimum value and SD is the standard deviation from optimum. For the 'more is better' situation, the value of "b" was set to -2.5, while for the 'less is better' state, it was assigned a value of +2.5, defining the steepness and direction of the curve.

These scoring equations standardize the soil property values, transforming them into a dimensionless score between 0 and 1. The 'more is better' scoring approach infers that higher values of the soil attribute are desirable, while the 'less is

better' scoring approach suggests that lower values are desirable.

Computation of SQI

To calculate the Soil Quality Index (LS-SQI), variable weights were derived from PCA-based communalities, representing each indicator's variance within the MDS (Nabiollahi et al., 2017). Each indicator's weight was the ratio of its communality to the total communality. Linear and non-linear scores were then multiplied by these weights to compute LS-SQI (Equation 3).

$$LS - SQI = \sum_{i=1}^n (W_i * LSi) \dots \dots \text{Equation 4}$$

LS-SQI is developed using linear scoring, LSi is linear scores of the ith soil attribute, and W_i is the communality-based weight of the ith soil attribute.

$$NLS - SQI = \sum_{i=1}^n (W_i * NLSi) \dots \dots \text{Equation 5}$$

NLS-SQI is developed using linear scoring, NLSi is linear scores of the ith soil attribute, and W_i is the communality-based weight of the ith soil attribute. Study is categorised based on SQI grades given Table 1.

The Soil Quality Indices (SQIs) were assessed using the Sensitivity Index (SI) as defined by Zornoza et al. (2008) (Equation 4). The SI is calculated by dividing the maximum SQI value (SQI(max)) by the minimum SQI value (SQI(min)).

$$SI = \frac{SQI(\max)}{SQI(\min)} \dots \dots \text{Equation 6}$$

The SI reflects the responsiveness of soil quality indicators to both management practices and environmental factors. A higher SI indicates greater sensitivity to natural and anthropogenic processes.

Results

Descriptive statistics

The physico-chemical and biological characteristics of soils along the Thonnur Kere distributary varied distinctly across the upper, middle, and tail-end regions (Table 2).

The upper region's sandy loam texture (sand: 63.63%) supported good aeration, moderate WHC (34.11%), and low bulk density (1.08 g/cm³). Slightly acidic to neutral pH, low EC (0.55 dS/m), and moderate organic carbon (1.04%) favoured microbial activity. High dehydrogenase and MBC levels indicated healthy soil biology, supporting optimal nutrient cycling and root growth (Brady & Weil, 2016 and Nair and Ghosh, 2021).

In the middle region, soils exhibited a loam texture with increased silt (25.53%) and clay (18.68%), improving WHC (38.99%) but raising bulk density (1.26 g/cm³) due to compaction. Moderate alkalinity (pH 8.03) and rising EC (0.76 dS/m) indicated salinity risks. Organic carbon declined (0.81%), while nitrogen (155.06 kg/ha) and phosphorus (24.66 kg/ha) increased. Iron (15.79 mg/kg) and zinc (0.44 mg/kg) decreased

under alkaline conditions. Biological activity reduced, with lower urease (32.05) and MBC (197.81), reflecting microbial stress.

The tail-end region showed finer texture, high WHC, and elevated bulk density, pH, EC, and sodium, indicating salinity-alkalinity stress. Declines in organic carbon, iron, zinc, and microbial activity (DHA, MBC, urease) signalled deteriorating soil health. These patterns reflect irrigation-driven degradation, emphasizing the need for targeted soil management to mitigate salinization and biological decline.

Correlation matrix

The correlation analysis among the soil physico-chemical and biological properties revealed several significant relationships that help understand soil quality dynamics as shown in **Figure 2**.

Sand and clay showed the strongest negative correlation ($r = -0.663$), indicating their inverse relationship in soil texture. Urease activity and microbial biomass carbon (MBC) were positively correlated ($r = 0.182$), reflecting microbial influence on nitrogen cycling. pH and electrical conductivity (EC) also showed a positive link ($r = 0.243$). Sulphur and organic carbon (OC) were positively related ($r = 0.203$), while dehydrogenase activity was negatively correlated with OC ($r = -0.222$), indicating possible microbial stress. In the middle region, MBC correlated positively with sodium ($r = 0.318^*$) and dehydrogenase with potassium ($r = 0.255$). Organic carbon linked with sulphur ($r = 0.203$), while clay and sand ($r = -0.663$) and calcium and iron ($r = -0.341$) showed negative correlations.

Correlation analysis showed dehydrogenase activity negatively related to bulk density ($r = -0.315^*$) and WHC ($r = -0.212$), indicating compaction hinders microbes. MBC was positively correlated with WHC ($r = 0.270^*$) and calcium ($r = 0.176$), suggesting better moisture and structure support microbes. Urease activity was negatively linked to zinc ($r = -0.286^*$) and potassium ($r = -0.250$), implying excess nutrients may suppress microbial function.

Assessment of Soil Quality Index

PCA and Minimum Data Set

The Principal Component Analysis (PCA) identified five principal components (PCs) with eigenvalues greater than 1, together explaining 43.63% of the total variance among the 20 soil physical, chemical, and biological properties in the upper region of the study area (**Table 3**). Among these, PC1 accounted for the highest variability (11.14%), followed by PC2 (9.09%), PC3 (8.40%), PC4 (7.81%), and PC5 (7.20%).

Principal Component Analysis (PCA) for the upper region identified five significant components explaining major patterns in soil variability. PC1, dominated by high negative loadings of Sand (-0.783) and MBC (-0.343) and positive loadings of Zinc (0.603) and Sulfur

(0.468), represents a “texture–micronutrient” axis, indicating that finer soils retain more micronutrients (Sharma et al., 2016). PC2 (9.09% variance) was defined by Water Holding Capacity (0.620), Calcium (0.515), Silt (0.468), and Sodium (0.402), reflecting a “moisture–cation availability” component, consistent with Lal (2020). PC3 showed strong influence from Dehydrogenase activity (0.522) and Nitrogen (0.390), with negative loadings for Organic Carbon (-0.413) and Potassium (-0.410), forming a “biological activity–nutrient dynamics” axis (Nannipieri et al., 2012). PC4 highlighted Iron (0.600) and Bulk Density (0.349) positively, and Clay (-0.457) and CEC (-0.440) negatively, suggesting a “compaction–iron availability” relationship. PC5 had high loadings from pH (0.616), MBC (0.441), and Urease (0.405), forming a “pH–biological activity” gradient, in line with Acosta-Martínez and Tabatabai (2000). Communalities and high factor loadings (0.522–0.783) confirmed that these PCs effectively captured soil variability. Based on loading strength and inter-correlation (<0.6), the Minimum Data Set (MDS) for this region includes Sand and WHC (physical), pH, EC, Fe (chemical), and Dehydrogenase activity (biological), representing key indicators for soil quality assessment (Lal, 1997; Andrews et al., 2002). Principal Component Analysis (PCA) in the middle region of the Kere Thonnur distributary identified five components explaining 42.15% of total variance. PC1 (10.91%) showed a textural gradient with high clay, silt, sulphur, and negative sand loadings. PC2 (8.41%) reflected base saturation and soil reaction, with positive calcium and pH, and negative iron and magnesium. PC3 (7.85%) linked microbial biomass carbon, EC, and silt. PC4 (7.67%) highlighted enzyme activity and exchangeable bases. PC5 (7.31%) emphasized organic matter and retention via CEC and OC. These components guide Minimum Data Set (MDS) selection for sustainable soil management.

Principal Component Analysis (PCA) for the tail-end region identified five principal components (PCs) with eigenvalues >1 , explaining 42.32% of total soil variance. PC1 (11.23%) showed high Sand (0.767) and negative loadings for Clay (-0.481), Sulphur (-0.486), and Zinc (-0.549), indicating a “textural–micronutrient contrast.” PC2 (8.76%) revealed a “moisture–cation–biological trade-off,” with WHC (0.608), Ca (0.550), and negative MBC (-0.495), Dehydrogenase (-0.343). PC3 (7.92%) reflected textural-chemical dynamics (Fe: 0.486, pH: -0.439). PC4 (7.44%) indicated “compaction–cation exchange” with BD (0.483) and CEC (-0.442). PC5 (6.98%) emphasized silt (0.613) and clay (-0.553) variation. Based on high loadings (≥ 0.5), low inter-correlations (<0.6), and 90% contribution, the MDS for this region includes Sand, Silt, Clay, WHC, BD, pH, CEC, Ca, and Fe, capturing key soil variability for informed management.

Assessment of Soil Quality Index (SQI)

The soil quality indicators selected for the Minimum Data Set (MDS) were classified into three categories: “more is better” (including WHC, OC, CEC, Exchangeable Ca, Available Fe and DHA), “less is better” (Na, Sand, and BD), and “optimum range” (pH and EC).

The scores for these indicators were calculated using two methods i) linear scoring method, as described in Equations (1) and (2) and ii) non-linear scoring, as described in Equations (3). Following this, the Soil Quality Index (SQI) was computed by applying the respective weights from Table 5, 6 and 7 for minimum data set of upper, middle and tail end region of study area along with the indicator scores, resulting in 6 index values three of each from linear scoring and non-linear scoring. SQI-ULS (based on linear scoring; Equation 4), SQI-MLS (based on linear scoring; Equation 4) and SQI-TLS (based on linear scoring; Equation 4) and SQI-UNLS (based on linear scoring; Equation 5), SQI-MNLS (based on linear scoring; Equation 5) and SQI-TNLS (based on linear scoring; Equation 5).

$$\text{SQI-ULS} = (\text{LS_Sand} * 0.255) + (\text{LS_WHC} * 0.208) + (\text{LS_pH} * 0.165) + (\text{LS_EC} * 0.192) + (\text{LS_Fe} * 0.178) + (\text{LS_DHA} * 0.192) \quad (5)$$

$$\text{SQI-MLS} = (\text{LS_Sand} * 0.255) + (\text{LS_Silt} * 0.186) + (\text{LS_OC} * 0.173) + (\text{LS_CEC} * 0.173) + (\text{LS_Na} * 0.182) + (\text{LS_Ca} * 0.199) + (\text{LS_Fe} * 0.199) + (\text{LS_DHA} * 0.182) \quad (6)$$

$$\text{SQI-TLS} = (\text{LS_Sand} * 0.265) + (\text{LS_Silt} * 0.165) + (\text{LS_Clay} * 0.165) + (\text{LS_WHC} * 0.207) + (\text{LS_pH} * 0.187) + (\text{LS_BD} * 0.176) + (\text{LS_Ca} * 0.207) + (\text{LS_Fe} * 0.187) \quad (7)$$

$$\text{SQI-ULS} = (\text{LS_Sand} * 0.255) + (\text{LS_WHC} * 0.208) + (\text{LS_pH} * 0.165) + (\text{LS_EC} * 0.192) + (\text{LS_Fe} * 0.178) + (\text{LS_DHA} * 0.192) \quad (8)$$

$$\text{SQI-MLS} = (\text{LS_Sand} * 0.255) + (\text{LS_Silt} * 0.186) + (\text{LS_OC} * 0.173) + (\text{LS_CEC} * 0.173) + (\text{LS_Na} * 0.182) + (\text{LS_Ca} * 0.199) + (\text{LS_Fe} * 0.199) + (\text{LS_DHA} * 0.182) \quad (9)$$

$$\text{SQI-TLS} = (\text{LS_Sand} * 0.265) + (\text{LS_Silt} * 0.165) + (\text{LS_Clay} * 0.165) + (\text{LS_WHC} * 0.207) + (\text{LS_pH} * 0.187) + (\text{LS_BD} * 0.176) + (\text{LS_Ca} * 0.207) + (\text{LS_Fe} * 0.187) \quad (10)$$

The Soil Quality Index (SQI) for selected sites fell under Grade I (>0.547), indicating “Very High” soil quality, with SQI scores ranging from 0.54–0.79 (linear) and 0.68–0.80 (non-linear), reflecting excellent conditions for sustainable agriculture (Table 6). The Sensitivity Index (SI) ranged from 1.17 to 1.46, showing high responsiveness of SQI to changes in soil parameters, confirming the robustness of the selected indicators and scoring methods. To assess soil quality variability, multivariate cluster analysis was conducted using key physical, chemical, and biological indicators. Clusters were validated using hierarchical clustering (to observe parameter

trends) and silhouette scores (to evaluate clustering quality).

The Soil Quality Index (SQI) assessed using linear (inner ring) and non-linear (outer ring) scoring methods revealed spatial variability across the Thonnur distributary (Figure 3). The **middle region** exhibited consistent SQI values (34%) under both methods, indicating balanced soil health with uniform distribution of soil quality indicators. In the **upper region**, non-linear scoring yielded a slightly higher SQI (30%) compared to linear (27%), suggesting that key indicators such as organic carbon or microbial activity may be approaching optimal thresholds, thus being better captured by non-linear models.

Conversely, in the **tail-end region**, linear scoring (39%) overestimated soil quality relative to non-linear scoring (36%), indicating possible sub-optimal performance of critical indicators not reflected in the linear approach. Overall, non-linear scoring provided a more ecologically relevant assessment of soil quality, highlighting the need for region-specific management strategies.

Figure 4 presents the hierarchical clustering and silhouette scores of soil properties in the upper region based on the Soil Quality Index (SQI). Twenty-five indicators were grouped into five clusters (C1–C5), revealing functional associations among physical, chemical, and biological attributes. Cluster 1 showed the highest mean silhouette score (~0.155), indicating strong cohesion and distinctiveness, making its indicators ideal for inclusion in the Minimum Data Set (MDS). Clusters 2 to 5 had lower scores (~0.045–0.08), with Cluster 5 showing the weakest cohesion, suggesting redundancy or limited functional relevance. Combining cluster structure with silhouette metrics refines SQI development by selecting indicators with both statistical distinctiveness and ecological significance.

The integrated interpretation of hierarchical cluster analysis (HCA) and silhouette scores provides valuable insight into the structure of soil quality indicators (SQIs) in the middle region (Figure 5). HCA revealed five distinct clusters reflecting functional relationships among soil physical, chemical, and biological properties. Clusters 4 and 5, containing indicators like Ca, Na, microbial biomass carbon (MBC), and dehydrogenase activity (DHA), had higher silhouette scores (~0.128 and ~0.138), indicating strong internal cohesion and distinctiveness. In contrast, Clusters 2 and 3 showed low scores (~0.04 and ~0.03), suggesting poor clustering and potential functional redundancy. Thus, indicators from high-scoring clusters should be prioritized for Soil Quality Index (SQI) development due to their strong discriminative power.

Similarly, in the tail-end region (Figure 6), five clusters emerged through HCA, highlighting inherent grouping among soil parameters. Clusters 3 and 4, including organic carbon, nutrients, water

holding capacity, and enzyme activities, showed high silhouette scores (~ 0.17 and ~ 0.19), confirming their ecological relevance and internal consistency. Conversely, Cluster 2, with near-zero silhouette score, displayed high variability. Integrating HCA with silhouette metrics supports the selection of statistically distinct and functionally meaningful indicators, enhancing the robustness of SQI-based land evaluation.

Discussion

Soil quality along the Thonnur Kere distributary shows marked spatial variability due to irrigation, land use, and landscape position. Textures shift from sandy loam upstream to loam/clay loam downstream, reflecting sediment deposition from canal flow and reduced gradient (Rao et al., 2010). This leads to higher water holding capacity (WHC) at the tail-end. Bulk density (BD) rises from 1.08 to 1.40 g cm^{-3} , likely due to compaction and reduced organic matter. Organic carbon (OC) declines from 1.04% to 0.50% , reflecting poor biomass return and decomposition—factors that affect aggregation and porosity (Six et al., 2002). Soil pH increases downstream, becoming moderately alkaline, with corresponding rises in EC and sodium due to salt accumulation and limited leaching (Minhas & Sharma, 2006).

Nutrients like nitrogen and phosphorus increase downstream due to transport from upstream applications, but micronutrients like Zn and Fe decline due to reduced availability at higher pH (Alloway, 2008). Biological activity—urease, MBC, and DHA—declines downstream due to salinity and reduced organic matter, with higher microbial activity in the upper reaches (Nannipieri et al., 2003).

Correlation analysis highlights key interactions: sand negatively correlates with silt ($r = -0.475$) and clay ($r = -0.663$) (Brady & Weil, 2016). MBC shows a positive link with urease ($r = 0.182$), and pH correlates with EC ($r = 0.243$), suggesting rising alkalinity with salinity (Sharma & Chaudhari, 2012). Notably, DHA and BD show an inverse relationship ($r = -0.315$) (Masto et al., 2006), while MBC and WHC correlate positively ($r = 0.270$) (Brockett et al., 2012). Other key associations include urease–Zn ($r = -0.286$), Ca–Fe antagonism ($r = -0.341$), and DHA–K ($r = 0.255$), reflecting nutrient interactions and microbial responses under salinity stress.

Key factors of soil quality were discovered via the use of Principal Component Analysis (PCA) and Minimum Data Set (MDS) selection. In each region, five principal components (PCs) accounted for over 42% of the variability. In the upper region, PC1 identified a “texture–micronutrient” axis, where sand was inversely related to micronutrients (Sharma et al., 2016). PC2 represented a “moisture–cation” relationship, while PC3 was shaped by biological indicators like DHA and nitrogen (Nannipieri et al., 2012). MDS

included both physical (sand, WHC) and biological (DHA) properties. In the middle region, PCA highlighted texture (PC1), pH and base saturation (PC2), and microbial and nutrient interactions (PC3–PC5), with MDS emphasizing MBC, EC, and DHA—supporting the inclusion of biological and chemical indicators (Andrews et al., 2002). For the tail-end, texture and micronutrient retention dominated, while moisture retention, compaction, and microbial processes defined other components (Franzluebbers, 2002). MDS here included sand, clay, BD, WHC, pH, CEC, Ca, and Fe.

The Soil Quality Index (SQI), computed using linear and non-linear scoring, classified all regions under Grade I (“Very High”) with values ranging from 0.54 to 0.79 (linear) and 0.68 to 0.80 (non-linear). Because non-linear scoring is sensitive to ecological thresholds, it produced somewhat higher SQI values (Qi et al., 2009). The top section is a vital monitoring zone because of its greatest Sensitivity Index (SI) of 1.46 , which suggests that little changes there might have significant effects (Velasquez et al., 2007). According to Nannipieri et al., 2012, these findings support the use of PCA–MDS frameworks and highlight the significance of including biological indicators such as MBC and DHA for sustainable soil management.

For the purpose of creating a strong Soil Quality Index (SQI), the combined examination of silhouette scores and Hierarchical Cluster Analysis (HCA) in the upper, middle, and tail-end portions of the Thonnur distributary provides thorough insights into the structural coherence, functional grouping, and selection efficiency of SQIs. This method improves the objectivity of choosing the Minimum Data Set (MDS) and takes into consideration the functional relevance and geographical variability of soil properties by combining statistical clustering with silhouette validation. Five unique clusters (C1–C5) of soil indicators were identified by HCA across all three locations, highlighting multivariate commonalities between physical, chemical, and biological characteristics. However, there were notable regional differences in the structural cohesiveness and clustering performance as shown by silhouette ratings.

In the upper region, Cluster 1 achieved the highest mean silhouette score (~ 0.155), reflecting strong intra-cluster similarity and inter-cluster dissimilarity. This suggests that the indicators within this group (e.g., pH, bulk density, CEC) are well-structured and non-redundant, thus making them ideal candidates for inclusion in the MDS. The relatively lower silhouette scores of Clusters 2 to 5 (ranging from ~ 0.045 to 0.08) suggest weaker clustering integrity, possibly due to overlapping functionality or high variability among indicators. These findings are in line with those of Andrews et al. (2002) and Karlen et al. (2001), who emphasized that indicators with higher clustering

fidelity should be prioritized to ensure the sensitivity and accuracy of SQI.

In contrast, the middle region demonstrated higher silhouette scores overall, particularly in Clusters 4 and 5 (~0.128 and ~0.138), which contained functionally significant indicators such as exchangeable Ca, Na, microbial biomass carbon (MBC), and dehydrogenase activity (DHA). The clustering of biologically and chemically active parameters in these high-scoring clusters suggests stronger ecological coherence and potential responsiveness to management. The relatively poor silhouette values of Clusters 2 and 3 (~0.04 and ~0.03) reflect limited discriminative power and potential redundancy, warranting cautious selection. These observations support findings by **Bastida et al. (2008)** and **Shukla et al. (2006)**, who advocated for the use of both structural validation and ecological function in selecting soil health indicators.

In the tail-end region, the clustering pattern revealed greater separation and internal consistency, especially in Clusters 3 and 4, which exhibited the highest silhouette scores (~0.17 and ~0.19) among all regions. These clusters grouped ecologically relevant indicators such as organic carbon, available macronutrients (N, P, K), water holding capacity, and enzymatic activities—key drivers of soil fertility and biological health, especially under terminal water stress. The superior silhouette performance here suggests that despite potential degradation or reduced fertility at the tail-end, these indicators maintain strong structural associations and relevance to soil functionality. Conversely, Cluster 2 showed a near-zero silhouette score, reflecting inconsistent groupings and poor reliability. These findings corroborate the works of **Lehman et al. (2015)** and **Cherubin et al. (2016)**, who emphasized the importance of biological indicators in distinguishing soil quality under stressed agroecological conditions.

Comparatively, the tail-end region exhibited the most coherent and functionally integrated clusters, likely due to stronger differentiation between well-performing and degraded soil parameters under moisture-limited environments. The middle region showed moderate clustering integrity, potentially benefiting from a balanced mix of soil inputs and moisture availability. The upper region, despite having favourable conditions, showed slightly weaker silhouette scores for several clusters, possibly due to functional redundancy or uniformity in soil properties, which reduces indicator contrast. Overall, the combination of HCA and silhouette scoring allows for a more informed and ecologically meaningful selection of indicators, ensuring that the final SQI reflects both statistical distinctiveness and functional relevance. This approach adheres to the framework recommended by **Doran and Zeiss (2000)** and **Karlen et al. (2003)** for soil quality monitoring—emphasizing

the integration of biological, chemical, and physical parameters that are not only statistically robust but also management-responsive.

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Declaration statement

The authors declare that they have no conflict of interest.

Data availability statement

Data will be provided on request basis

Funding statement: There are no relevant financial or non-financial competing interests to report.

Conflict of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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